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Predictive Analytics for Demand Forecasting – A Comparison of SARIMA and LSTM in Retail SCM

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Abstract

The application of predictive analytics (PA) in Supply Chain Management (SCM) has received growing attention over the last years, especially in demand forecasting. The purpose of this paper is to provide an overview of approaches in retail SCM and compare the quality of two selected methods. The data used comprises more than 37 months of actual retail sales data from an Austrian retailer. Based on this data, SARIMA and LSTM models were trained and evaluated. Both models produced reasonable to good results. In general, LSTM performed better for products with stable demand, while SARIMA showed better results for products with seasonal behavior. In addition, we compared results with SARIMAX by adding the external factor of promotions and found that SARIMAX performed significantly better for products with promotions. To further improve forecasting quality on the store level, we suggest hybrid approaches by training SARIMA(X) and LSTM on similar, pre-clustered store groups.

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Keywords: Predictive Analytics; Demand Forecasting; Machine Learning; Supply Chain Management

1. Introduction

Predictive analytics (PA) in Supply Chain Management (SCM) has received growing attention over the last years. Especially in retail supply chains (SC), volatile customer demands, fierce competition and complex global supply network structures require efficient processes and data-driven decisions [1, 2]. Particularly high potential of applying PA in retail SCM is seen in the context of demand forecasting. Accurate and sophisticated demand forecasts enable informed decisions in inventory management, purchasing, assortment planning and ultimately ensure product availability at the point of sale [3]. Decreasing fulfilment times force companies to utilize new technologies and

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advanced analytics in the industry 4.0 era. Huge amount of data is generated and provided by these technologies, which in turn allow for increase data utilization and exploitation to make data-driven decisions. Especially in the context of demand forecasting in industry 4.0 this represents an essential opportunity [4].

In the last years, a growing body of literature emphasized a "horses for courses" approach in context of selecting most suitable forecasting methods for different settings and types of data [5]. However, answering the question of which method best suits available data in a given context remains a challenge for practitioners and researchers.

The current paper focuses on this issue and provides an overview of currently used demand forecasting approaches and a detailed comparison of two selected methods. The paper builds on real-life data from a large-scale research project in the area of data analytics in retail SCM. The project consortium consists of university partners and one of the main grocery retailers in Austria with stores across the country. In order to provide a concise focus, the paper emphasizes on perishable products and more precisely on fruits and vegetables. Recent studies show that miscalculated forecasts lead to high volumes of perishable items being discarded. Despite this, retailers frequently experience out-of-stock (OOS) situations, especially for perishable items like fruits and vegetables. The dichotomy of having to throw excessive amounts of products away on the one hand but still facing OOS on the other hand represents a crucial challenge for retailers. Not only does this results in a waste of natural resources and non-sustainable outcomes but it also leads to customers leaving stores if desired products are unavailable [6]. The current paper hence addresses the following research question: *How do selected predictive analytics approaches for forecasting the demand of fruits and vegetables in grocery retail perform in terms of forecasting quality?* To answer this question, an extensive data analysis in the course of an applied research project was conducted, aiming at exploring the quality and performance of different algorithms in practice (cf. section 3).

The remainder of the paper is structured as follows: section two provides the results of an extensive literature review on the usage of different forecasting methods in different domains. Section three introduces the methodological steps of the paper and presents the data basis used, the details of data cleaning and preparation as well as the specifics of data modelling. Subsequently, section four discusses the demand forecasting results of two selected methods and compares their performance and applicability in the context of predicting the demand of fruits and vegetables. Finally, section five concludes the paper and provides an outlook on future research.

2. Literature review – Overview of Demand Forecasting Methods in Retail SCM

Demand forecasting in retail SCM affects a broad array of domains and process levels and provides vital intelligence for supply chain managers as decision support. Especially in the retail sector, demand volatility hugely impacts retail networks and their ability to perform in an efficient yet responsive way [7]. Inaccurate demand forecasting results in either overstock or understock problems. Overstocking leads to non-sustainable actions, perished products, blockage of storing space and needles handling and planning effort. Understocking in turn results in OOS, which results in product unavailability and decreased customer satisfaction. Hence, accurate demand forecasting is vital for managing optimal purchasing and inventory levels, reducing OOS and acting in a more sustainable and efficient way [8]. This is especially true for grocery retailing and perishable items with limited shelf life [9].

Demand forecasting can be conducted on a short-term (6 to 12 month) or long-term level (more than one year). The common goal of these forecasting methods is to discover data patterns and provide forecasts as accurately as possible. Machine learning techniques are amongst the top quantitative methods and allow for processing huge amounts of input data to create accurate, adaptable and transparent outcomes [7].

Machine learning techniques applicable for forecasting can be clustered into three categories: i) time series analysis, ii) regression-based methods and iii) supervised and unsupervised methods [7]. Time series analysis-based approaches are the most popular ones and include e.g. autoregressive integrated moving average (ARIMA) or Holt Winter Exponential Smoothing (HW). Especially in retail demand forecasting, these approaches are highly acknowledged due to their capability to capture trends and seasonal demand behavior [8,10]. Previous research applied ARIMA-based models in the context of predicting the daily sales of onion in Indian grocery retail [11]. Results indicated higher demand patterns for onion on Mondays. Veiga et al. [12] compared ARIMA and HW models to forecast daily sales of dairy products in a retail company in Brazil. They showed inter alia that HW methods provide more accurate results for predicting demand over complete season periods.

Many retailers still conduct manual forecasting based on their experiences to predict product demand levels for the next day [10]. However, besides being time-consuming and strongly depending on the individual experiences and biases, that approach may not always be trustable due to dependency of customer demand on many external factors [13]. Such external factors can be controllable like price variations, substitution and cannibalization or uncontrollable like holidays, seasons and weather [10]. Bratina and Faganel [14] proposed ARIMAX method to predict daily sales of beer in Slovenia based on retailers' sales data. They considered external factors like temperature, New Year occasion and price in their model. Later, Lee et al. [15] utilized the same method to analyze the effect of Islamic holidays on monthly sales of boys' clothes in Indonesia. Dellino et al. [16] developed ARIMA, ARIMAX and transferred function models in order to forecast daily sales of 156 perishable food items of 19 retailers based on a three-year data set. They aimed to improve the reliability of the forecasts by considering external factors like price and concluded that the performance of each method is highly dependent on the quality of the data set. However, in their study, transfer function models have shown better flexibility and reliability. Arunraj et al. [8] belived that seasonal ARIMA (SARIMA) approaches have better forecasting result for seasonal time series without outlying data. To capture this problem, they combined SARIMA models with external factors such as holidays and promotions and proposed a new method named SARIMAX to predict the daily sales of perishable items in German retail stores. The results confirmed that enriching SARIMA with external factors improved prediction accuracy. Hirche et al. [17] analyzed the effect of temperature on weekly sales of alcoholic beverage in 37,346 retail stores in the US with SARIMAX methods over a three-year period. The result of their analysis showed that sale levels of beer, liquor, red and white wine indicate higher temperature sensitivity than other wines like rose and sparkling. They also noticed that holidays and geographic location affect alcoholic beverage sales [17].

Regression based methods as the second group of forecasting techniques can consider independent and dependent variables. Taylor [18] conducted an exponentially weighted quantile regression (EWQR) to predict daily sales of an outlet supermarket chain in UK. Ög et al. [19] provided a forecasting model based on a regression tree technique for grocery stores and proved that considering promotions increases the accuracy of prediction results[20].

As mentioned before, time series analyses are the most common approach for demand forecasting in literature, however, these methods cannot capture nonlinear behavior of data. The third group of methods for demand forecasting, which includes supervised and unsupervised models like artificial neural networks (ANN) or long short-term memory (LSTM), addresses this issue. Alon et al. [21] compared ANN with traditional methods like HW, ARIMA, and regression models for predicting monthly sales of retail products. In their study, ANN performed better than the traditional methods. Aburto and Weber [22] combined ARIMA models and neural networks (NN) to forecast customer demand of a Chilean supermarket. In another study they combined NN and ARIMA to develop a hybrid intelligent system for retail sales forecasting [23]. The performance of NN model was better than ARIMA and the combined model showed the best results. Zhang and Sun [13] proposed a combined forecasting model named LightGBM-LSTM. In their model, LightGBM method was developed based on Gradient Facilitated Decision Tree (GBDT) to deal with the problem of large sales dataset, and LSTM method has been utilized to capture nonlinear relationship of data. Abbasimehr et al. [24] developed a multilayer LSTM network to forecast customer demand of a furniture company. Compared with real time series data, their method had better performance than other methods such as ANN and ARIMA. Another study compared the accuracy of Long short-term memory (LSTM) with traditional methods like SARIMA, HW seasonal and Fourier seasonal models to forecast daily sale of fresh fish [10]. In order to provide an overview of previously used demand forecasting methods and techniques, the following table 1 provides a summary of previous studies on demand forecasting in the retail sector.

Table 1. Literature Review

Reference	Year	Methods and techniques	Domain	external variables
[21]	2001	ANN, HW, Box Jenkins ARIMA, and multivariate regression	retail sales	
[22]	2003	naïve, seasonal naïve, unconditional average, SARIMAX, and several neural network models	Chilean supermarket sales	payment, intermediate payment, before holidays, holidays, festivals, school vacation, climate, price

[18]	2007	EWQR	fashion retail in UK	
[23]	2007	NN and ARIMA	Chilean supermarket sales	holidays, end of month
[14]	2008	ARMAX	beer sales on Slovenian market	weather temperature, new year and price
[19]	2009	Regression Tree	grocery stores sales	promotions
[15]	2010	ARIMAX, SARIMA, NN	Muslim boys' clothes sales in Indonesia	Islamic holidays
[11]	2013	ARIMA	vegetable (onion and potato) sales in an Indian wholesale market	
[12]	2014	ARIMA and HW	dairy products sales	
[16]	2015	ARIMA, ARIMAX and transfer function models	fresh food sales	price
[8]	2016	SARIMAX	German food and fashion retail sales	price, promotions, holidays and festivals
[25]	2017	MLP, BayesianNetwork, LR and SVM	warehouses demand of national dried fruits and nuts company from turkey	
[20]	2018	Baseline Simulation, LR, Decision Regression Tree and Random Forest Regression	bread in an online supermarket sales	
[26]	2019	SARIMA, Weighted Least Squares	fashion retail sales	brand, gender, whether the item is seasonal or permanent, age group and product type
[10]	2020	LSTM, SARIMA, HW and Fourier seasonal modelling	fresh fish sales	price and holidays
[13]	2020	LightGBM-LSTM	vegetables sales	
[27]	2020	Gradient-boosted regression trees (GBRTs), ANN	German bakery retail sales	holidays and special days
	2020	ARIMA, ETS, ANN, KNN, RNN, SVM and single layer LSTM	a furniture company sales	
[17]	2021	SARIMAX	alcoholic beverages sales	weather, holiday, location

3. Research Method – Data Selection, Date Preparation and Data Modelling

The abundance of forecasting methods shows the vast range of their applicability in different areas. In accordance with the research question of the paper, this section introduces the details of the available data, the steps taken to prepare and clean the data as well as the selected data modelling approach. Based on the relevance of external factors – especially that of promotions as discussed in the previous section – their effect on forecasting accuracy is also analyzed in detail. It has to be mentioned, that it is not possible to record or calculate the real customer demand in food retail stores (because customers cannot place orders and can only buy actually available products). As a consequence and in accordance with Ahrens et al. [8], the actual product sale level in the provided data is considered as the real demand.

3.1. Data Selection and Understanding

The employed data is related to cashier data of four perishable products sold in more than 90 stores of a selected region of a leading retailer in Austria. As introduced, an emphasis is laid on fruits and vegetables. More precisely, the sale levels of the most purchased vegetables in the sub-groups of tomato, potato, salad, and cucumber over a period of three years from January 2017 to December 2019 were selected as the data basis for the paper. Figure 1 illustrates the historical daily sales of these four products. Significant sale peaks are mostly related to promotions:

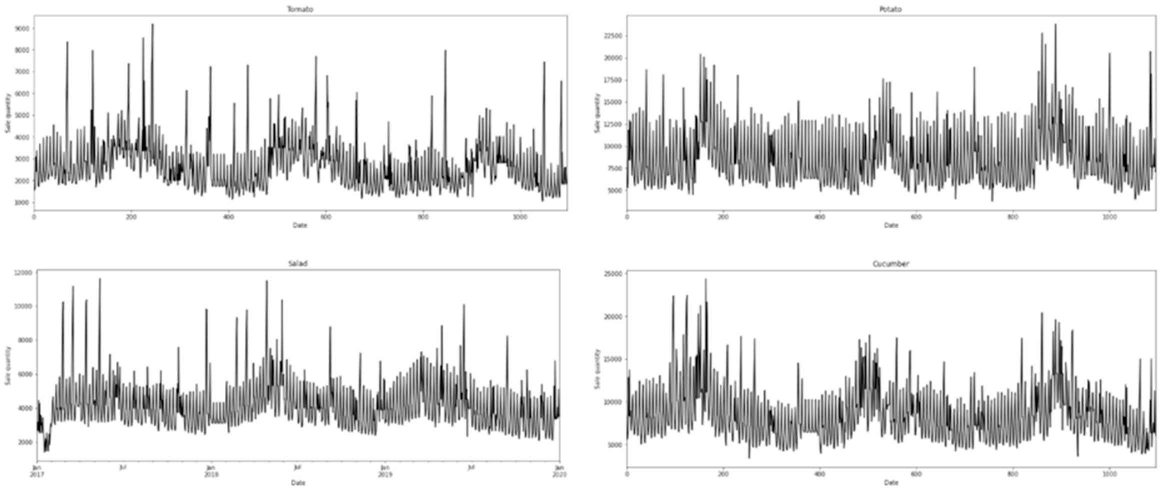

Figure 1. Daily sales of all stores

As mentioned, price variations could change customer demand. Such variations can either be planned promotions or unplanned price reductions [8]. Although both of these changes can encourage customers to buy products, unplanned changes in the price are usually applied on current stock (and hence on current, unprepared stock levels) and huge changes in sale records are not visible due to OOS at the point of sale. In contrast, in planned price reductions days which we are further referred to as “promotion days”, stores are prepared for potentially higher sale levels and hence increase stock levels in advance. Therefore, there is a significant growth in average daily sales during promotion days. In this paper, we focus on planned price reduction only, as there is a significant dependency of sale levels and the external factor of promotion days:

3.2. Data Preparation and Cleaning

Three years of historical sale data out of the cashier data records for each product were selected. If three days in a row showed more than 25% price reduction in the cashier data, it was regarded to as promotion days. Subsequently, to analyze their effect, product promotion days are appended to the time series as an external factor.

Data preparation in this step is needed not only to smooth noises, but also to recognize trends and seasonality [9]. Hence for days with missed sale values, we tried smoothening the noises and replace missing data with simple arithmetic average (SAA) method [28]. In formula (1) $\hat{Y}_{m_k t}$ represents the calculated missed value and $Y_{m_k N}$ is the available data in the homologous day for other years.

$$\hat{Y}_{m_k t} = \frac{1}{N}\left(Y_{m_k 1} + Y_{m_k 2} + \cdots + Y_{m_k N}\right) \tag{1}$$

To recognize noisy data, we have used time series decomposition. If the recognized noise was bigger (or smaller) than the average plus two standard deviations of sale and did not belong to any promotion days or holidays, the data was smoothed similarly to the method of filling missed data.

3.3. Data Modeling – Model Selection

Finding the best forecasting model in time series analysis has always been a big challenge for decision makers [29]. Since historical sales data of stores can be considered as time series data, we have selected two of most popular time series forecasting methods in literature as discussed and presented in section two of the paper. More precisely, SARIMA(X) was selected as a parametric and LSTM as a non-parametric model to provide sale predictions for the selected vegetables for month of January 2020 based on the data of the years 2017, 2018 and 2019. Subsequently, the selected methods are described.

3.3.1. SARIMA

Autoregressive integrated moving average (ARIMA) is a famous linear model that is used for forecasting problems of linear time series [12]. It is expressed by (p,d,q) in which p is for autoregressive terms, q is related to moving average terms and d is non-seasonal differences. The main advantage of seasonal ARIMA (SARIMA) model is its ability to consider seasonal behavior of stationary or non-stationary time series [8].

3.3.2. SARIMAX

The main limitation of SARIMA is its inability in considering outlying data caused by external variables. To answer this problem, SARIMAX has been proposed by researchers. SARIMAX is a SARIMA model with external parameters [8].

3.3.3. LSTM

Neural networks are a type of artificial intelligence methods that model complex nonlinear relationships between response and predictor variables. Recurrent neural networks (RNN) is a type of artificial neural network in which signal flows of neuron-to-neuron is not limited to moving in one direction. It is suggested as a reliable method for series forecasting [24]. Long short-term memory (LSTM) is a type of RNN that can keep information in long memory from sequential observation [24]. This method describes properties of the data without any prior knowledge of parameters and distribution. The independency of this model to the parameters makes simpler adjusting to the complex and nonlinear series [30].

3.4. Data Modeling – Model Implementation

In this research, the best parameters for SARIMA models were obtained with Autoarima function and the models were optimized with Statsmodels package in Python. The initial step to implement Autoarima is selecting appropriate m. As mentioned before, the parameters are selected with the help of time series decomposition and expert interpretation. The value for m in our models are 7, 7, 5, and 12 for Salad, Potato, Cucumber and Tomato respectively. To implement single layer LSTM models, we need to normalize data. Minmaxscaler from sklearn library in Python was used to scale the data between 0 and 1. Keras library, Adam optimizer and rectified linear unit activation have been utilized for this model. For each model (SARIMA and LSTM) and product (salad, tomato, potato, and cucumber) the optimal parameters are provided in Table 2.

Table 2. Optimal parameters for each model

Product	LSTM: best loss	SARIMA: (p,q,d) (P,Q,D)
Salad	0.0023	(3, 1, 0) (1, 0, [1], 7)
Tomato	0.0057	(5, 1, 4) (1, 0, [], 12)
Potato	0.0044	(3, 1, 0) (1, 0, [1], 7)
Cucumber	0.0024	(3, 1, 3) (2, 0, [1], 5)

3.5. Data Modeling – Model Evaluation

To evaluate the models, we used mean absolute percentage error (MAPE) [31] and root mean square deviation (RMSE) [24]. To this end, the following formulas were applied, in which y_t shows the observed value at time t and $\hat{y}_t$ represents the forecasted value. Details regarding the interpretation of the MAPE [31] is presented in Table 3.

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(\hat{y}_t - y_t)^2} \quad (2)$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|\hat{y}_t - y_t|}{y_t} \quad (3)$$

Table 3. Interpretation of MAPE

MAPE	Interpretation
<10	Highly accurate forecasting
10-20	Good forecasting
20-50	Reasonable forecasting
>50	Inaccurate forecasting

4. Results and Discussion

As explained, three years of historical sales data as recorded in the cashier data were considered as training data to which the models have been fitted. The fitted models have subsequently been used to forecast the sales of the following month of January 2020 and compared to the actual sale levels as recorded in the cashier data for this month. In order to analyze the effect of promotions on sale, we have added promotion days of the following month and integrated them into our model. Figure 2 illustrates the comparison of predicted daily sales for the selected products by applying LSTM (blue line), SARIMA (green line) and SARIMAX (yellow line) with actual sales in January 2020 (black line). Considering promotions as an external factor has increased the accuracy of prediction in almost all models.

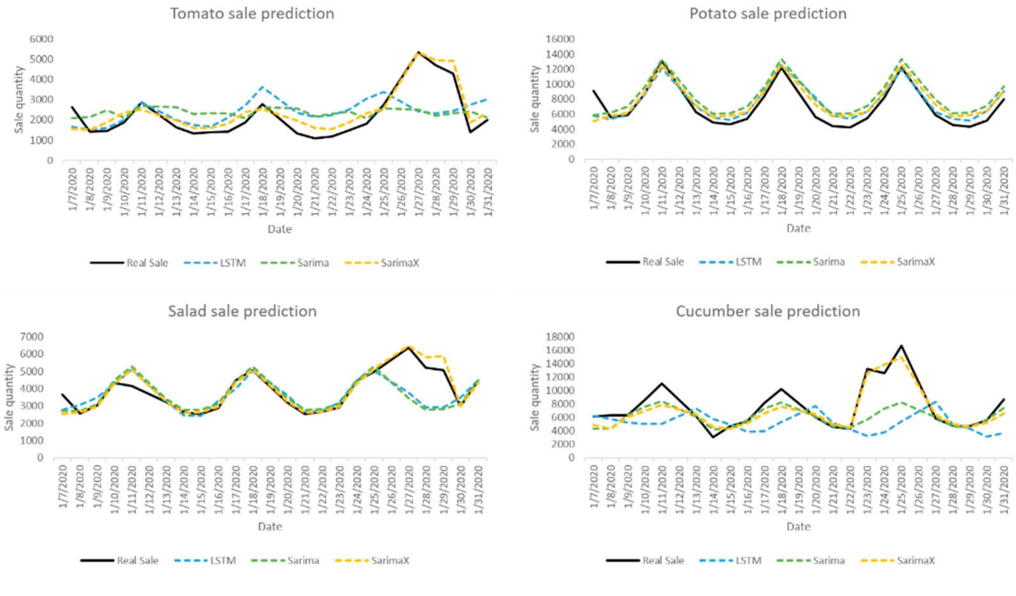

Figure 2. Model prediction comparison

To evaluate reliability of each model, MAPE and RMSE have been calculated and are presented in Table 4. To have a more precise evaluation, we conducted the evaluation on the test part of the dataset.

The comparison of actuals sales for the three years shows that the accuracy of SARIMA and LSTM are close to each other for the selected products salad and tomato. However, the performance of SARIMA is significantly better for cucumber and contrary wise for potato, for which LSTM produced better results.

To identify possible reasons for these results, we looked at the historical sale behavior of the selected products. As shown in **Error! Reference source not found.**, historical sales data for potato and salad show a more steady trend and are free of intensive noise. For product with these characteristics and a stable behavior, our result reveal that LSTM models can provide good prediction results, which is in line with [10][24].

Regarding the forecast accuracy for tomato, the MAPE is much higher (however, still at the “reasonable forecast” level) than for the other products (which are mostly at the “good forecast” level, cf. Table 3). At first glance, we found out that the tomato sale levels did not follow its historical trend in January 2020. As we only analyzed the top-selling type of tomatoes, a wider variety of different tomato types in 2020 could be one source for this weird behavior. For example, similar organic products in this product group have been observed in the cashier dataset, which wasn’t the case for the other three products.

For cucumber, SARIMA model provided a good forecasting, while LSTM results were only reasonable and did not fulfil our expectations. The source of this abnormally could be related to the fluctuating behavior of this product. This can be recognized in **Error! Reference source not found.**, where the range of noises for cucumber is much wider than that of other products.

Table 4. MAPE and RMSE of all methods on test data

Product	Method	MAPE	RMSE	Rank MAPE	Rank RMSE
Salad	LSTM	14	949	2	1
	SARIMA	13	1009	1	2
Tomato	LSTM	44	1170	1	2
	SARIMA	48	1163	2	1
Potato	LSTM	15	1184	1	1
	SARIMA	25	1626	2	2
Cucumber	LSTM	35	4502	2	2
	SARIMA	16	2854	1	1

In the second step of our analysis, we tried to implement SARIMAX model in order to consider promotion days as an external factor. The results are satisfying, and we experience a big improvement in the accuracy of predictions compared to normal SARIMA model. However, these improvements are not similar for all products. As it is observable in Table 5, the improvement via SARIMAX is highly correlated to changes of daily sale averages in promotion days, where we experience a significant improvement for salad and tomato, where the improvement was 53% and 54%. In contrast, the moderate improvement of potato results (28%) may be related to a lower correlation of potato sales and promotion days. In addition, there were no promotion days for this product during January 2020 and the model was not able to show its advantages in this period. For cucumber, the results showed an even lower improvement (12,5%) by adding the external factor of promotion days. Possible reasons for that could be unidentified degrees of dependency between cucumber sale levels and other external factors like holidays or substitute products, which could be higher than for the other three products. In summary, SARIMAX results improved demand predictions for salad from good to highly accurate, for tomato and potato from reasonable to good. For cucumber demand prediction, the forecasting quality improved and stayed at the level of a good forecast.

Table 5. Comparison of SARIMA and SARIMAX models

Product	Method	MAPE	RMSE	Promotion days sale /Normal days sale	MAPE reduction
Salad	SARIMA	13	1009		
	SARIMA + Promotions	6	389	1.8	53%
Tomato	SARIMA	4	1163		
	SARIMA + Promotions	22	446	2.1	54%

Potato	SARIMA	25	1626		
	SARIMA + Promotions	18	1309	1.5	28%
Cucumber	SARIMA	16	2854		
	SARIMA + Promotions	14	1352	1.8	12.5%

5. Conclusion and Outlook

Accurate demand forecasting in perishable products could increase the competitive power of a retailer and improve its performance. A wide range of forecasting methods has been implemented in businesses with different reliability. In this paper, we tried to analyze the performance of two most common analytics approaches (SARIMA and LSTM) to predict daily sales of four vegetable products relating to a leading retailer in Austria. Following this goal, first, we tried to select the appropriate parametric or nonparametric method of forecasting based on the characteristics of the data and business knowledge for the related product. Second, we improved forecasting results using additive external factors.

MAPE and RMSE measures have been used to evaluate the reliability of forecasted sale values. Considering this, both models provided results in the range of reasonable or good forecasting. However, it is clear that the accuracy of predictions is highly dependent on the quality of data. For instance, sales forecasting results of both models for tomato couldn't meet our expectation where the recent behavior of tomato is not following the historical path relating to new domains of operation such as introducing bio or organic products. In general, in the given datasets, LSTM performed better for products that have more stable historical data (e.g., potato), while SARIMA model produced more reliable results for products with seasonally repeating behavior (e.g., cucumber).

As promotions can notably increase sales of selected vegetables, we tried to investigate how considering this external factor can improve our forecasting results. To this purpose, SARIMAX method was employed, where promotions were added to SARIMA model as an external variable. As expected, the results improved significantly. Though, it is assumed that for some products (e.g., cucumber), there may be other influential external factors that would have to be considered to further improve forecasting quality. For potato, that did not have any promotion days during the forecasting period, LSTM prediction results were still closer to real sales.

Therefore, in cases of close results (e.g., in our case for SARIMA and LSTM for salad and SARIMAX and LSTM for potato), selecting a more applicable method is a matter of taste. Understanding the characteristics of data as well as time and business input limitations before conducting data analysis is crucial. SARIMA models require more statistics background while LSTM models rely more on the calculation performance of the computer hardware. SARIMAX method on the other hand proved its ability in coping with data noises caused by external variables. However, implementing this method requires deep knowledge of businesses to understand external inputs, for instance, recognizing special days and estimating their duration effect.

The result of this paper can improve the profitability of businesses by increasing the sale number and decreasing the amount of waste products based on the usage of complex methods of forecasting. The improved forecasting models can be used by businesses to optimize their inventory level, increase their bargaining power for purchasing, and ensure product availability. In the context of industry 4.0, advanced demand prediction represents an important prerequisite and enabler. Various papers have already dealt with this issues at the intersection of industry 4.0 and demand forecasting and found huge implications e.g. in the context of energy demand prediction and energy savings [32, 33], demand prediction for automated warehouse management [34], demand prediction based on product tracing and customer feedback [35] or demand prediction based, automated purchase orders and production [36]. The potential changes enabled by advanced, PA-based demand prediction are hence huge and may show in industry 4.0 in the form of automated production and purchase order planning, more efficient warehouse management and higher availability of products. Especially in the retail sector, this results in reduced out-of-stock situations at the point-of-sale and subsequently in higher availability, customer satisfaction and turnover. Furthermore, in the context of food retailing highly precise demand prediction reduces product wastage, the need for quality-related product discounts and ultimately enables more sustainable retail practices by neither being out-of-stock nor over-stock. However, in traditional industries where e.g. one-piece production is the standard norm, quantitative data for training demand prediction algorithms could be less available and hence prediction results could show to be less reliable. Future research could focus on such areas and could especially analyze how PA can also be applied there.

The limitation of this paper is first, that it only focusses on the vegetable products of one retailer in Austria. Implementing the same methods for different market players would show the level of repeatability of our results. Second, we have used forecasting methods for selected items of product groups. This simplification could underrate the importance of cannibalization and the effect of substitution. Third, we have compared the forecasting results with the actual sales. It is recognizable in figure 2, that for some days, especially in the peaks, forecasting has surpassed actual sales. However, it could not be identified if this lower number of sales is related to lower customer demand or to product shortage. To improve the accuracy of the prediction, more time series forecasting methods should be tested in the future. Also, future studies could focus on examining the effect of other external factors such as calendar events or weather as well as availability and promotions of substitute products. Moreover, calculating products' demand on the level of single stores takes a big effort. To overcome this problem, the application of machine learning methods as basis for hybrid analysis approaches are suggested to deepen forecasting at the level of single stores. For instance, clustering the stores based on their sale behavior, and training the models for each cluster separately could increase the quality of forecasting models.

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